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A survey on QoS mechanisms in WSN for computational intelligence based routing protocols

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Abstract

With the rapid development in ubiquitous smart sensors, wireless sensor networks have started to evolve into numerous applications including healthcare, medical, agriculture, transportation, industry, internet of things, and smart cities. However, satisfying Quality of Service (QoS) requirements of the diverse application domains remains a challenging issue due to heterogeneous traffic flows, dynamic network conditions, and resource-constrained nature of sensor nodes. In this regard, application-specific QoS provisioning techniques have received considerable research attention at the network layer. This paper presents a systematic review on the QoS mechanisms that have been employed by routing protocols and also highlights the performance issues of each mechanism. Afterwards, the survey presents a comparative analysis of computational intelligence based QoS-aware routing protocols with their strengths and limitations. Finally, this survey discusses various potential directions for future research in the field of QoS provisioning at network layer.

Keywords Quality of Service (QoS) · Computational intelligence (CI) · Routing protocol · Wireless sensor network (WSN)

1 Introduction

The recent advancement in low power electronics, and ubiquitous smart sensors have made wireless sensor network (WSN) as one of the most significant technologies over the past decade. In most cases, a WSN integrates automated sensing, processing, and wireless transmission units into small electronics devices known as sensor nodes [1]. These nodes scatter randomly and densely over the geographical areas to sense various environmental parameters viz. temperature, pressure, humidity, sound, moisture, and seismic events. The sensed information is routed hop-by-hop towards the more potent node, referred as sink to further processed and analyzed [2]. Senor based applications have started to involve in various platforms and areas, including military surveillance, industrial and home automation, healthcare monitoring, underwater navigation, and environmental monitoring. Recently, researchers have received have realized some specific denominations for various WSN application domains [3] as shown in Fig. 1. For instance, sensor networks used for transmitting video, audio, and images particularly for surveillance and monitoring purposes may be called as wireless multimedia sensor networks (WMSNs). Sensor networks deployed inside factories or industries for machine condition monitoring and process automation termed as industrial wireless sensor networks (IWSNs). When used for medical and healthcare, the network can be labelled as wireless body area networks (WBANs). In addition, when sensor nodes deployed underwater to facilitate underwater navigation, surveillance, pollution monitoring, and disaster prevention, are termed as underwater wireless sensor networks (UWSNs). Finally, when sensor nodes are mobile, they may be called as mobile sensor networks (MSN). These application domains have different constraints in their nature and requirements which require QoS assurance in terms of delay, reliability, energy-efficiency, bandwidth utilization, adaptivity, scalability and throughput [4–9]. Hence, providing QoS assurance in resource limited environment is one of the critical challenges that are addressed either by modifing the existing routing protocols in WSNs

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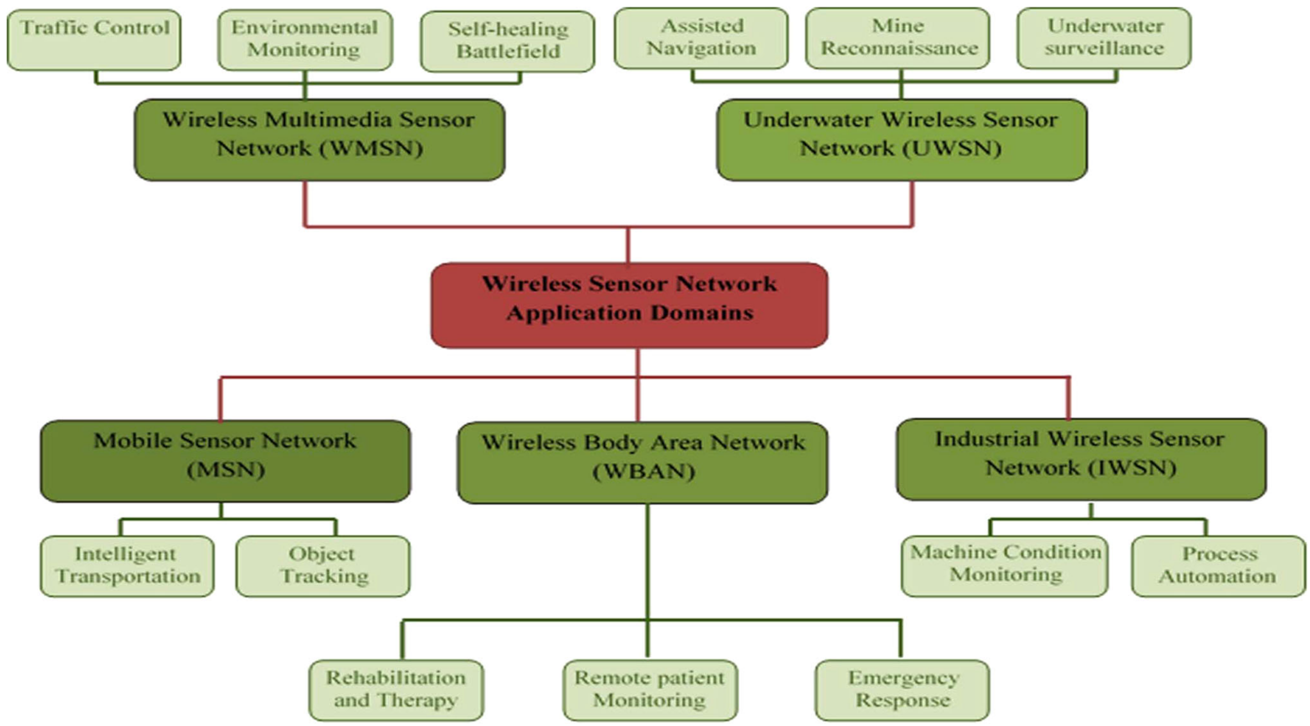


Fig. 1 Applications of WSN

or by proposing new QoS provisioning techniques, for example, multi-constrained routing, clustering, multipath routing, multiple sinks, and mobile sink. Therefore, this survey explores the recently proposed QoS mechanisms employed by routing protocols in WSN.

With the quick expansion of computational intelligence (CI) over the past decade [10–12], routing protocols based on particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), evolutionary algorithms (EA), fuzzy logic (FL), reinforcement learning (RL), and bee mating optimization (BMO) have been proposed to provide the application-specific QoS assurance in WSN. An idea of using computational intelligence in WSN is to provide flexibility and robustness towards network failure, dynamic network topology, and variable channel conditions in WSN. Thus, in this survey recently proposed CI based routing protocols is surveyed that provide QoS support at the network layer in WSN.

1.1 Survey contributions

The major contributions of this survey are summarized as below:

1. We provide an outline of QoS metrics that can be addressed at the network layer in WSN.
2. A broad overview on issues affecting QoS provisioning at the network layer is presented.
3. A detailed description on the various QoS mechanisms employed by routing protocols in WSN.
4. A detailed analysis of computational intelligence based QoS-aware routing protocols with their objectives, QoS mechanisms, operations, and simulation/experimental results is presented.
5. We provide a comparative analysis of CI-based QoS-aware routing protocols with emphasis on the QoS metrics along with their strengths and limitations.
6. We provide an insight into the future research directions that can improve the use of QoS provisioning techniques in WSN.

The rest of the paper is structured as follows. Section 2 presents a review of existing surveys on QoS-aware routing protocols in WSN. Section 3 discusses commonly employed network layer QoS metrics, followed by the issues affect QoS provisioning. Section 4 describes the QoS mechanisms employed by routing protocols. In Sect. 5, the CI- based QoS-aware routing protocols are briefly discussed. Section 6 provides a comparative and analytical analysis of the reviewed protocols. Finally, Sect. 7 presents the conclusion and insights into future research directions.

2 Related work

While going through the literature, we analyzed that despite the considerable research on QoS-aware routing protocols, only a few surveys have been presented. Surveys [4, 13–16] are the prominent surveys that focus on providing QoS assurance at the network layer in WSNs. In [4], a literature on the real-time QoS and WMSN routing protocols was presented. The reviewed protocols were classified on the basis of the number of routing metrics used to locate the optimal path between source and destination. In [13], energy-efficient routing protocols for WMSN were overviewed and grouped into two categories based on the QoS requirements: latency and multi QoS constrained. In [14], authors presented a taxonomy of multipath routing protocols classified on the basis of path utilization mechanisms for real-time WMSNs. They also investigated the design issues for multipath strategy at the routing layer. In [15], QoS-aware routing protocols were surveyed for WBAN. Based on the network architecture, the authors classified the surveyed protocols into two categories: Multi-sink approach-based design and Single-sink approach-based design. QoS aware routing protocol related to every classification were compared based on their operations, advantages, and shortcomings. Real-time QoS routing protocols were briefly discussed in [16] for WMSNs. The studied protocols were arranged into two categories: probabilistic and deterministic protocols. Every classification was further grouped into hard and soft protocols for the real-time environment and compared based on QoS features, strengths, and limitations. Authors also examined issues associated with real-time QoS assurance in WMSNs.

Although a plethora of surveys on routing protocols [17] are presented over the past decade. Most of these surveys are limited in the context of reviewing the classical routing protocols in WSN. Further, none of the existing survey have provided the proper taxonomy on the network layer mechanisms that allow for QoS provisioning in WSN. Therefore, the present survey is an attempt to write a systematic review on the recently proposed QoS mechanisms employed by the routing protocols in WSN. This survey presents a detailed analysis on computational intelligence based QoS-aware routing protocols with their objectives, operations, advantages, and limitations. Moreover, a brief comparison of computational intelligence techniques at the network layer is also presented. This comparison allows readers to select an appropriate CI technique to meet the desired QoS levels for the emerging WSN applications.

3 QoS metrics and challenges

With the rapid development in low power electronics and ubiquitous smart sensors, wireless sensor networks (WSNs) have started to evolve into wide range of monitoring and tracking applications. These applications are associated with various requirements of which a QoS routing protocol should be aware in an attempt to meet them. However, satisfying the strict QoS requirements of the emerging modern applications in the resource-constrained environment induces new challenges to the routing protocols. Thus, this section presents a brief outline on the most common QoS metrics that can be fulfilled at the network layer and the issues affecting the QoS provisioning in WSN.

3.1 QoS metrics at network layer

The level of QoS provisioning at the network layer is depend on several parameters, often termed as QoS metrics. It represents the QoS requirements of diverse WSN applications. An application may demand a particular QoS by specifying its requirements in terms of one or more QoS metrics. Thus, defining an appropriate QoS metrics used for a specific application is considered as a challenging task. The most common QoS metrics that can be considered at the network layer are summarized below [14, 17]:

1. *Energy efficiency* It is considered as the most predominant QoS requirement because of the battery-operated sensor nodes. Network layer can contribute to energy efficiency by employing various mechanisms such as clustering, multipath routing, or multiple sinks according to the application requirements.
2. *Latency* It is characterized as the delay experienced by a source node packet until it reaches the sink node. Network layer can achieve minimum latency or end-to-end delay by exploring shortest path among the source and the sink during the data packet transmission.
3. *Reliability (PDR)* It is characterized as the ability of the network to transmit real-time information to the sink node with the least packet loss. Reliability at network layer can be guaranteed by establishing multiple route among the source and the sink for redundant packet transmission under dynamic network conditions.
4. *Throughput* It is defined as the rate of successful packet delivery over the communication link. Thus, high throughput should be taken into consideration while proposing a routing protocol for real-time applications.
5. *Network lifetime* It is characterized as the number of communication rounds until the first node dies (FND), or a specific level of nodes dies. The FND metric is

usually adopted in sparsely deployed WSNs. However, in densely deployed WSNs, exhaustion of a single node would not affect network connection and sensing activity. Thus, in large or densely deployed WSN, metrics such as HND (half node die) and LND (last node dies) are also considered for the network lifetime evaluation.

6. *Adaptivity* The data traffic load, network topology, and wireless channel conditions may vary frequently due to node mobility, wireless channel noise, and failure probability of sensor nodes (example: nodes get disconnect from the network due to battery depletion). Therefore, a QoS mechanism must take into account the continuous adaptation of network operation parameters in order to support the highly dynamic environment.
7. *Robustness* It is defined as the ability of the routing protocol to reconfigure the network connectivity against sensor node and communication link failures. In harsh environments, sensor nodes are usually inclined towards the failure because of fast exhaustion of their battery power or some hardware component malfunctions. So, failure of a node disrupts the network connectivity not only with the sink but also with the neighbor sensor nodes. Thus, a routing protocol is required to be robust against the sudden failure of the sensor nodes.

3.2 Issues affecting QoS in WSN

Since WSNs are adopted in a wide range of monitoring and tracking applications, they have multiple characteristics associated with hardware and communication system which induces certain problems for QoS provisioning. The most predominant of these issues which influence the QoS in WSN are summarized as follows [4, 17]:

1. *Sensor node constraints* Since the quantity of nodes in WSN can be in hundreds or thousands, it is essential to design a sensor node, which constrains its abilities in terms of battery capacity, storage, computation, and network communication range. Therefore, providing QoS assurance in a resource-constrained environment is considered as a challenges issue.
2. *Dynamic network topology* The network topology may vary frequently due to addition and removal of nodes in the network, node mobility, and node failure. Therefore, dynamic network topology can cause an additional challenging issue for QoS provisioning in WSN.
3. *Scalability* It is the capacity of the network to effectively deal with the developing measures of information load. As the quantity of sensor nodes expands, the unpredictability to deal with the measure of information detected by nodes will get increased. Therefore, the designed QoS mechanism needs to operate well in the large-scale networks.
4. *Heterogeneous traffic* In WSNs, sensor nodes may generate heterogenous data traffic such as streaming videos, images, and periodic data packets. Therefore, multiple traffic flows, and differentiated requirements of each traffic flow imposes another challenging issue to achieve differentiated QoS in routing protocols.
5. *Redundant information* The distributed behavior of sensor networks allows sensor nodes to transmit redundant information to the sink node. This redundant information transmission guarantees reliability at the cost of extra energy utilization. Thus, data aggregation techniques must be introduced to maintain a strategic distance from the redundant data transmission. However, this may simultaneously introduce an extra delay in the network and this can impact QoS provisioning.
6. *Unreliable wireless channel* The radio channel quality in WSN may be affected by different environmental factors such as noise, multipath fading, shadowing, and the capture effect. These issues need to be considered in order to ensure reliability in WSN.
7. *Energy balance* Energy-efficiency is the important consideration in the design of energy-constrained WSN. The imbalanced traffic load distribution over the sensor nodes during the data packet forwarding may lead to the early energy depletion of the loaded sensor nodes. Thus, a QoS mechanism should uniformly adjust the energy consumption load among the sensor nodes along the route to the sink.

4 QoS mechanisms at network layer

This section describes the basic mechanisms which can be employed by routing protocols to provide QoS in resource-constrained WSN. Each of the QoS mechanisms has ability to accommodate the impact of different QoS issues and supports different QoS metrics based on the application. QoS mechanisms included in Fig. 2 are discussed in detail in the following subsections.

4.1 Service differentiation

Service differentiation [18] is the most predominant technique for QoS provisioning in resource-constrained WSN. It effectively shares the constrained network resources among the different traffic loads by prioritizing the traffic based on one or more criteria such as remaining hop count, remaining time to deadline, residual energy, traffic load, and distance traveled and forms several traffic classes.

Fig. 2 QoS provisioning techniques at network layer

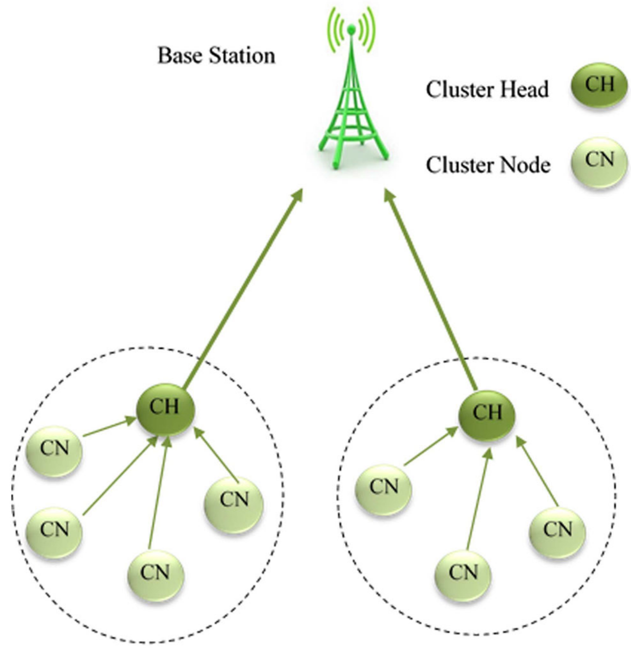


Fig. 3 Cluster and cluster heads

Thereby, network layer considers each of these traffic classes independently by establishing an optimal route for each of the traffic class and tries to meet the QoS requirements imposed by the significance of their carried data.

Since the poor prioritization of the traffic classes causes underutilization of network resources, it becomes hard to provide QoS assurance in a resource-constrained environment. Thus, an effective service differentiation mechanism should be taken dynamic priority assignment and dynamic network conditions into consideration.

4.2 Clustering

Clustering the nodes is an imperative mechanism in WSNs that provides QoS assurance in terms of energy efficiency and reliability [19]. Clustering divides the network into small sized clusters, in which each cluster has a cluster head (CH) and member nodes as depicted in Fig. 3. Once the network is set-up, the communication between the nodes is characterized into intra-cluster and inter-cluster communication. The member nodes send their data to the associated CHs, and the CHs then forward aggregated data to the BS either directly or via multi-hop routing. In the recent past [20, 21], different clustering methods have been presented which improve energy-efficiency via various means: (i) By reducing the range of communication among the clusters which require less transmission power, (ii) By reducing the network load through data aggregation, (iii) By adjusting the energy consumption load among the nodes via CH rotation, (iv) By using sleeping schemes in which the CHs are awake and rest of member nodes follow the sleeping schedule, (v) By using TDMA based medium access mechanism to perform intra-cluster communication without collisions. Besides energy-efficiency, clustering provides significant improvement in the network scalability by maintaining a hierarchy in the network.

However, in multi-hop approach, CHs near to the BS deplete their energy very rapidly because of high inter-cluster relay traffic load, causing the hot-spot problem. In this respect, algorithms with an unequal clustering support should be further investigated to address the hot spot issue in WSN. Moreover, in hierarchical WSN, the failure of a CH node disrupts the network connectivity not only with its associated member nodes but also with the neighbor CHs nodes. Therefore, clustering algorithms need to be considered a fault-tolerant issue in an attempt to maintain the network connectivity and maximize the network lifetime.

4.3 Multiple routing metrics

Multi-constraint QoS routing has come across as one of the imperative techniques to support real-time services in WSN. Routing metric is a parameter used to select the best optimal relay node and network path towards the sink node [22]. In order to meet the application-specific QoS constraints at network layer, several routing metrics have taken into consideration such as delay, reliability, hop count, traffic load, and residual energy for optimal route selection.

However, finding an appropriate routing metrics while maintaining an efficient mathematical cost function have been turned out to be an NP-complete issue, because the optimization of one metric leads to the deprivation of another and also increase in number of routing metrics increases the complexity of route computation [13]. Although changing network dynamics makes difficult for routing protocol to maintain updated information in resource-constrained WSN.

4.4 Multiple sink

In large-scale WSNs, if a single sink is located at an area that might be far from the source nodes, there is the probability that the network performance degrades very quickly. This is because the residual energy of sensor nodes near to the sink get drained at much faster rate as compared to the far away sensor nodes and hence, leads to the early isolation of the sink. Moreover, data transmission through multiple intermediate nodes may be expensive in terms of E2E transmission delay. Therefore, by deploying multiple sinks across the field, data transmission rate becomes faster, and the energy of nodes remains conserve as the data packets are not required to propagate through multiple hops to reach the sink [23]. However, for multiple sinks deployment, it is imperative to locate the optimal number and the position of the multiple sink nodes in an attempt to limit the transmission delay while maintaining minimum energy consumption.

4.5 Mobile sink

In WSN architecture, when a static sink node is used, sensor nodes close to the sink exhaust their battery rapidly as compared to other nodes, leading to premature network failure. The mechanism of introducing mobile sink to the WSNs framework has received adequate consideration in recent years to maximize the network lifetime [24, 25]. With the deployment of mobile sink in the network, the hotspots around the sink change constantly with its movement and hence, the probability of each node to become the neighboring node of the sink is also increased. This results in the data traffic load distribution around the mobile sink. However, the movement pattern of the sink node is extremely essential for the execution of WSNs. The controlled sink mobility improves network connectivity, coverage, and reliability of data reporting in sparse and partitioned architectures. With uncontrolled sink movement, the network routes towards the sink node changes very frequently, which introduces significant communication overheads in terms of energy and delay. Moreover, this may also lead to the route failure among the source and the sink because of the weak communication range. Thus, an efficient routing recovery mechanism which determines an optimal trajectory for the mobile sink is required to be considered in the mobile sink WSNs.

4.6 Multipath routing

The idea of using multipath routing in WSNs is to deliver QoS support to heterogenous traffic load by distributing the traffic load along the multiple paths based on their QoS requirements. The traffic distribution also balances the energy consumption load and reduces the probability of network congestion by alternating the forwarding nodes among source and sink. Furthermore, multipath routing can maintain the network reliability by redirecting the network traffic load towards another active node in the case of primary route failure [26]. However, multipath routing may expand the complexity of WSN as it involves appropriate strategies for fragmentation and defragmentation of multimedia video streaming routed over multiple paths.

Table 1 summarizes the advantages and disadvantages of the described QoS mechanisms employed by routing protocols in WSN.

5 Computational intelligence based QoS-aware routing protocol

Computational intelligence provides an adaptive mechanism that induces intelligent behavior in a dynamic and complex environment like WSNs [27]. In recent years, with the quick expansion of CI techniques, routing protocols based on ant colony optimization, fuzzy logic, particle swarm optimization, artificial bee colony, evolutionary algorithms, reinforcement learning, and bee mating optimization have been widely adopted to ensure application-specific QoS guarantee in the resource-constrained WSN [10, 11]. Such routing protocols have proved to work well under WSN-specific requirements such as network failures, dynamic topology, and node mobility. In this section, we discuss intelligent algorithms based QoS-aware routing protocols in WSN.

5.1 Ant colony optimization

ACO [28] is a swarm intelligence technique which is inspired from the intelligent and foraging behavior of real ants in nature. The ants collaborate with each other through an inter-mediator referred as the pheromone. It is a volatile chemical material secreted by the ants while hunting down the food source. The intensity of the pheromone trail is used to locate the shortest path from their habitat towards the food source. ACO comprises of two working insect models known as forward ant and backward ant. Forward

Table 1 Comparison of QoS mechanisms at network layer

QoS mechanisms	Key ideas	Advantages	Limitations
Service differentiation	Prioritizes and differentiates the network traffic into several traffic classes according to the significance of carried data	Supports heterogenous traffic load Effectively shares the available constrained resources among the different traffic classes	Requires dynamic priority assignment Not adaptable to dynamic network conditions
Clustering	Splits the network into small sized clusters, in which each cluster has a cluster head and member nodes	Ensures load balancing Improves network scalability Avoids redundant data transmission	Suffers from hot spot problem Requires fault tolerance mechanism
Multiple routing metrics	At network layer, several routing metrics have taken into consideration for optimal relay node selection towards the sink node	Effectively meets the application-specific QoS requirements in resource-constrained environment Ensures load balancing	Selecting an appropriate routing metrics is still remained as the NP-complete problem
Mobile sink	The controlled sink mobility increases the probability of each node to become the neighboring node of the sink	Balances traffic load Improves network coverage and scalability Ensures reliable data delivery	Suffers from large control overheads High probability of route failure due to uncontrolled sink mobility
Multiple sinks	Deploying more than one BSs over the geographical area to avoid the early isolation of a single BS	Balances the energy consumption load Improves network scalability Faster the data transmission rate	Difficult to locate the optimal number and the position of the multiple sink nodes
Multipath routing	Distributes the network traffic along the multiple paths towards the destination	Ensures load balancing Maintains network reliability Effectively support heterogenous traffic load	Requires appropriate strategies for fragmentation and defragmentation of multimedia video streaming

ants generate probabilistic solution based on two parameters; pheromone trail and heuristic information [29]. The probability of kth ant selecting a decision point j from decision point i is evaluated as follows.

$$P_{ij}^{k} = \left\{ \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{j=1}^{N}[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}} \right. \tag{1}$$

where pheromone value τ_{ij} indicates the posterior information of the previously attained potential solution, the heuristic value η_{ij} indicates the prior information of the promising solution, α and β are the two weight parameters which control the impact of pheromone and heuristic qualities, respectively, and N represents the set of current neighboring decision points of decision point i.

Once all the forward ants reach the destination, they switch to the backward ants and thoroughly update the pheromone concentration on the traversed path while traveling towards the nest. The pheromone update on an edge is evaluated as follows

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t+1) \tag{2}$$

where ρ represents the pheromone evaporation rate, τ_{ij} represents the quantity of the pheromone laid by the ants on edge (i,j), and $\Delta\tau_{ij}(t+1)$ represents the pheromone quantity deposited by ants on edge (i,j) for the current iteration. Though each ant is capable of constructing a potential solution, the high-quality solution will result through the global cooperation between the members of the ant colony [29]. Figure 4 explains the operation of the ACO algorithm.

Cai et al. [30] proposed an ACO based QoS-aware routing protocol called ACO-QoSR in WSN. ACO-QoSR protocol uses the intelligent searching feature of artificial ants to resolve the delay constrained QoS routing issue in a fully distributed manner. It determines the optimal routing path by exploiting a trade-off between path delay and residual energy ratio (ERR) of sensor nodes. Once the existing path is broken, the intermediate nodes quickly search for the backup routes to maintain a strategic distance from any network interruption. Moreover, it mitigates stagnation by integrating pheromone restricting and pheromone smoothing strategies in the convention ACO algorithm. This integration limits the pheromone concentration on non-ideal routes and furthermore avoids the generation of dominant paths. Simulation results demonstrate that ACO-QoSR protocol ensures significant reduction in the path delay and the energy consumption while maintaining the least routing overheads. However, it doesn't consider

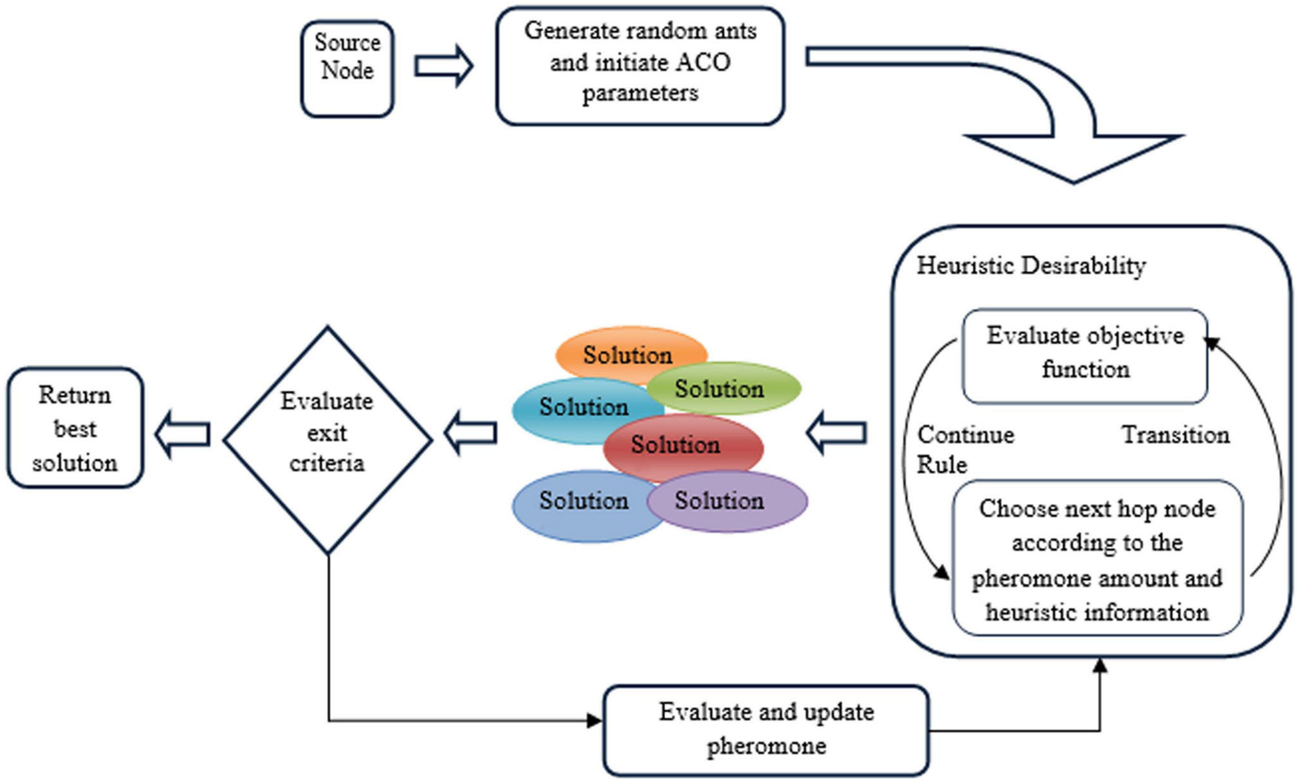
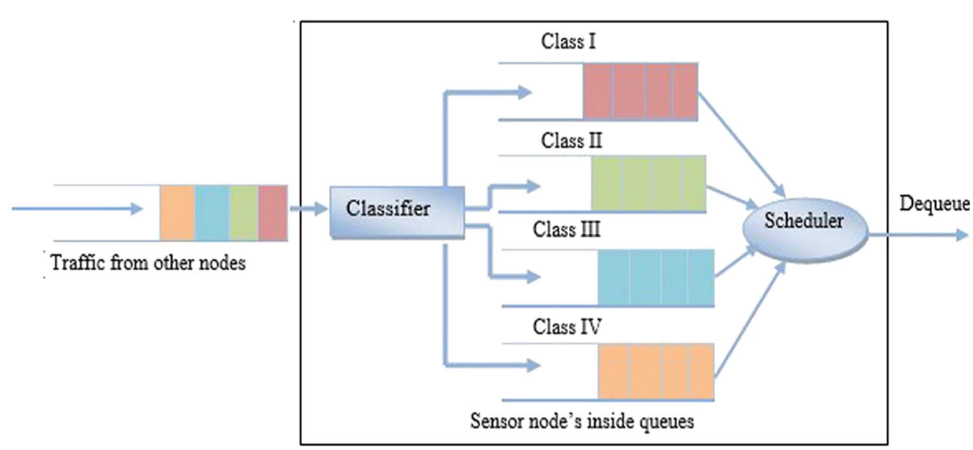


Fig. 4 Ant colony optimization

the energy utilization because of retransmission of data packets under the dynamic network conditions.

Cobo et al. [31] proposed an AntSensNet protocol which integrates hierarchical architecture with an ACO-based routing to meet the QoS prerequisites of WMSNs. It is a hybrid routing protocol that considers reactive as well as proactive components for efficient route establishment. It supports various kind of multimedia media traffic classes with diverse QoS requirements as shown in Fig. 5. This is achieved by introducing a packet scheduling policy which considers different priorities for each traffic class and subsequently determines multiple paths that satisfy different QoS requirements, such as delay, remaining energy, and packet loss. AntSensNet protocol also introduces an efficient multi-path video packet scheduling mechanism in an attempt to reduce congestion in the video packet transmission. Moreover, the hierarchical nature of AntSensNet protocol reduces the collision among the member nodes for data transmission and improves its performance as far as energy efficiency and latency. Simulation results reveal significant improvement in delivery ratio, energy efficiency, and E2E delay when compared with the conventional AODV protocol for heterogeneous traffic load. Nevertheless, AntSensNet protocol generates

Fig. 5 Queuing model of AntSensNet protocol



separate ants for control packets (FANT, BANT), data packets (DANT), videos (VFANT, VBANT) and clustering (MANT) which leads to large routing overheads and high complexity.

Zuo et al. [32] proposed a hybrid multi-path routing algorithm called DAWMNet for IWSNs. DAWMNet algorithm integrates ant colony with dijkshtra's algorithm for reliable and deterministic data transmission. Dijkstra's algorithm determines shortest route across the source nodes and the gateway during the initial route setup, while ACO algorithm explores multiple redundant paths for data transmission through pheromone diffusion and updation. In addition, DAWMNet algorithm also has the ability to handle the route failure due to dynamic topological changes by performing the route maintenance mechanism. Simulation results reveal the effectiveness of the DAWMNet algorithm in terms of E2E delay, delivery ratio, and routing overheads when contrasted with the conventional multipath routing protocols. However, its efficiency decreases with increase in a number of dead nodes, particularly in small-scale networks.

Tong et al. [33] proposed an ACO based multipath routing protocol known as EAMR, which exploits the intelligent searching of real ants for optimizing the energy and delay constrained WSNs. It is based on the hybrid routing approach which is reactive during the route establishment mechanism and proactive during the route maintenance. Initially, the source node establishes multiple paths by broadcasting the forward ants. Once the forward ants reach the destination, they switch to the backward ants and thoroughly update the pheromone concentration on the traversed path based on remaining energy of the path, hop count towards the sink node, and path congestion. This pheromone updating process achieves load balancing by distributing the traffic along multiple paths based on the estimated quality of path. Moreover, EAMR algorithm also has ability to recover the link failure caused either by high data traffic or by high node mobility. Through the extensive simulations, authors have shown that EAMR protocol outperforms in terms of E2E delay, and delivery ratio as contrasted to AOMDV and EEABR protocols. However, it generates high routing and control overheads during route establishment.

Malik et al. [34] introduced an enhanced ACO based QoS-aware routing protocol called EAQHSeN for heterogeneous WSNs. EAQHSeN protocol has the ability to meet the diverse QoS constraints of heterogeneous traffic load associated with multimedia and scalar sensor nodes. This is achieved by exploring independent routing path for each type of data traffic load. For multimedia data traffic, EAQHSeN protocol considers residual bandwidth and E2E delay as the heuristic factor for the selection of the next hop node which is defined as follows:

$$P_{ij}^{d} = \frac{(\tau_{ij})^{\alpha}(b_{ij})^{\beta}\left(t_{ij}^{d}\right)^{\beta}}{\sum_{k\in N_i^d}(\tau_{ik})^{\alpha}(b_{ik})^{\beta}\left(t_{ik}^{d}\right)^{\beta}}, \quad \alpha,\beta \geq 1 \tag{3}$$

where P_{ij}^{d} indicates the probability of selecting a node j, τ_{ij} indicates the pheromone concentration for node j, b_{ij} and t_{ij}^{d} are a measure of bandwidth and E2E delay, respectively.

For scalar traffic, residual energy (e_j) is considered as the heuristic factor for next hop node selection which is defined as follows:

$$P_{ij}^{d} = \frac{(\tau_{ij})^{\alpha}(e_j)^{\beta}}{\sum_{k\in N_i^d}(\tau_{ik})^{\alpha}(e_k)^{\beta}}, \quad \alpha,\beta \geq 1 \tag{4}$$

Simulation outcomes show significant improvement in data delivery ratio, E2E delay, and residual energy when compared with the standard AODV and EEABR protocols. Moreover, EAQHSeN achieves robust adaptation under the highly dynamic environment dictated by node mobility.

Wang et al. [35] proposed an improved ACO based algorithm called IACO-MS which integrates clustering and mobile sink technologies to address the hot spot problem in the static network environment. The modified ACO in IACO-MS routing algorithm improves the global search ability and accelerates the convergence rate of conventional ACO. IACO-MS routing algorithm determines an optimal traversal path for mobile sinks for data collection by taking into account the distance between the CHs and distance to other mobile sinks. The distance heuristic factor efficiently reduces the transmission delay and the energy consumption of CHs. Simulation results demonstrate significant improvement in network lifetime, energy efficiency, transmission delay when compared to the ACO-M routing algorithm. Nevertheless, IACO-MS algorithm does not have the ability to handle the link failure due to the node mobility.

5.2 Particle swarm optimization

PSO [36] algorithm originates from the social conduct of bird flocking, and fish tutoring. It comprises a swarm of predefined particles say N_P in search space, where a particle i occupies a position $X_{i,d}$ and a velocity $V_{i,d}$ in the dth dimension of global search space. During the search space, every particle monitors its own personal best called $pBest_i$ and a global best known as $gBest$ in a swarm. After finding the $pBest_i$ and $gBest$, a particle P_i updates its velocity and position in each iteration by using Eqs. (5) and (6) respectively.

$$V_{i,d}(t+1) = w \times V_{i,d}(t) + c_1 r_1 \left(pBest_{i,d} - X_{i,d}(t)\right) + c_2 r_2 \left(gBest - X_{i,d}(t)\right) \quad (5)$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \quad (6)$$

where w indicates the inertial weight, r_1, r_2 indicate two uniformly distributed random number and c_1, c_2 indicate two non-negative constants called acceleration factor commonly set to 2.0.

After getting a new position in each iteration, the particle P_i is evaluated by computing fitness function and accordingly updates its $pBest_i$ as well as $gBest$ as follows

$$Pbest_i = \begin{cases} P_i & if(fitness(P_i) < fitness(Pbest_i)) \\ Pbest_i & Otherwise \end{cases} \quad (7)$$

$$Gbest = \begin{cases} P_i & if(fitness(P_i) < fitness(Gbest)) \\ Gbest & Otherwise \end{cases} \quad (8)$$

This process is iteratively repeated until a fixed number of iterations $I_{\max}$ is reached. Figure 6 clarifies how a particle accomplishes a global optimum solution $gBest$ that reflects the best estimation of fitness particle by exploring the search space. In Multi-constrained QoS routing, PSO iteratively finds the best optimal path to meet the desired QoS requirements [37].

Liu and Sun [38] proposed an agent-assisted based QoS-aware routing protocol called QoS-PSO in WSN. It exploits the intelligent searching features of particle swarm to provide application-specific QoS. The QoS-PSO algorithm selects synthetic QoS as the objective function which incorporates numerous parameters, for example, delay, bandwidth, and packet loss for optimal path selection. The intelligent searching agents of the QoS-PSO algorithm can effectively adopt changes in network topology, and routing status of the node. These agents establish and maintain the route towards the sink node. Simulation results show that

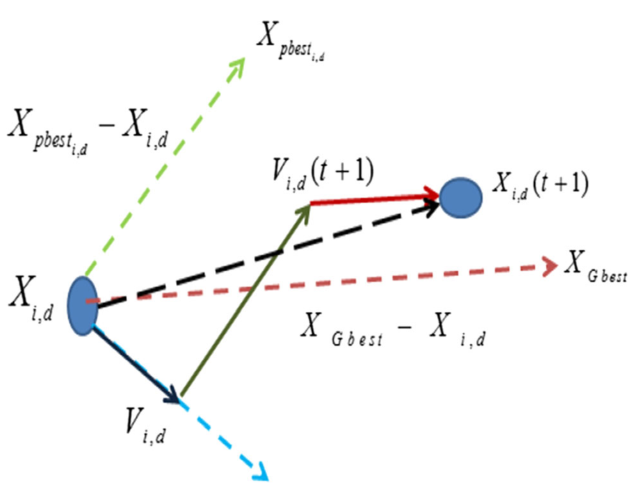


Fig. 6 Particle representation in PSO

QoS-PSO algorithm outperforms AODV and EEABR, in terms of delay, packet loss, and synthetic QoS. However, it doesn't consider the residual energy of sensor node while making the routing decision which may lead to the high energy consumption.

Hu et al. [39] proposed an effective routing recovery mechanism called ECPSOA which adopts endocrine cooperative PSO based algorithm to address the route recovery problem with minimum communication overheads. This is accomplished by incorporating multiple mobile sinks in the network for data accumulation. These multiple mobile sinks create a virtual backbone in order to establish reliable communication path for data collection. Once the primary links fail either due to sink mobility or complete energy depletion of the source nodes, the mobile sink establishes an alternate path with high residual energy, less transmission delay, less route distance and low energy consumption to avoid any network disruption. The endocrine mechanism in PSO enhances the global searching capability of the particles and accelerates the speed of convergence. Simulation results show significant improvement in communication overheads, energy consumption, network delay, and robustness against the route failure. Nevertheless, the alternate route selection in ECPSOA with multiple mobile sinks increases the computational complexity of the routing protocol.

Since conventional PSO is designed for continuous optimization problems, it does not have the ability to compute the discrete optimization problems. To address the discrete routing problem, Yang et al. [40] proposed GMDPSO, a greedy discrete PSO algorithm associated with memory for mobile WSNs. GMDPSO algorithm employs a greedy forwarding scheme to construct the optimal routing tree which requires path delay, and energy utilization as the QoS metrics for relay node selection. Once the primary path associated with source node is breakdown due to relay node failure, the route recovery mechanism of GMDPSO algorithm quickly establishes an alternate routing path to minimize the network delay. Besides, the improved greedy forwarding routing, the discrete PSO in GMDPSO algorithm redefines the position and velocity of the particle under discrete scenario and consequently redesigns the particle updating rule by considering the network topology. The discrete PSO mechanism accelerates the global convergence rate and produces high-quality solutions with minimum control overheads. Simulation results show significant improvement in robustness and adaptability towards the dynamic network topology while maintaining energy consumption and communication overheads at the minimum level.

In order to address the hop spot problem in static WSN, Wang et al. [41] introduced a PSO based clustering algorithm based on PSO with a mobile sink called EPMS.

EPMS algorithm integrates mobile sink and virtual clustering techniques to minimize latency and maximize network lifetime. The virtual clustering in EPMS algorithm considers residual energy and location of nodes for better CH election. After cluster formation, the mobile sink broadcasts Hello packets to the CHs for data collection and the CH with maximum residual energy in its communication range is selected for data transmission. Simulation results show significant deterioration in energy consumption and transmission delay while maximizing the network lifetime. Although, the fault tolerant mechanism of the EPMS algorithm restores the network connectivity by determining the broken path but can simultaneously induce significant communication overheads.

5.3 Artificial bee colony optimization

ABC algorithm exploits the foraging behavior of honey bees for optimizing multi-variable function problem [42]. In the ABC algorithm, honeybees forage for food source in the search space. The location of a food source in search space indicates a possible solution for the multi-constrained optimization problem and its nectar amount indicates the quality of the solution associated with the food source. The honeybees in ABC algorithm can be arranged into three gatherings: employed bees, onlookers bees, and scout bees. The employed forager bee exploits a food source within its neighborhood based on local information and its fitness cost. After each employed forager's honeybees complete the entire search, they share the fitness information of the food source such as direction, distance, and profitability with the onlooker honey bees, through a waggle dance. An onlooker bee evaluates the fitness (nectar) information provided by the employed bee and chooses a food source with a higher probability of nectar being found. After certain forages, when some of the existing food sources abandon by the employed bees, scout bees start searching for new food sources randomly around the hive [43]. Thereby, ABC algorithm achieves global optimization through exploration which is performed by artificial scouts, while attains local optimization through exploitation which is executed by onlookers and employed bees.

Karaboga et al. [44] exploited the intelligent behavior of honey bees to design an optimized clustering mechanism in WSN. Initially, authors have proposed ABC based clustering algorithm for WSN called CWA, which selects optimal CH by taking into consideration the effects of both intra-cluster and inter-cluster distance (f^{dist}). The fitness function of CWA is calculated as follows

$$f^{CWA} = f^{dist} \tag{9}$$

Then, authors modify the proposed fitness function by taking the battery level of nodes (f^{energy}) in order to extend the lifetime of the network. The fitness function of improved CWA (ICWA) is given by Eq. (10).

$$f^{ICWA} = \beta \cdot f^{dist} + (1-\beta) f^{energy} \tag{10}$$

where β is the weighing parameter. In order to introduce the quantity of service in their proposed fitness function (ICWAQ), the authors consider the packet delivery during the data gathering process. The fitness function of ICWAQ is given by Eq. (11).

$$f^{ICWAQ} = f^{ICWA} + f^{QoS} \tag{11}$$

$$f^{QoS} = \left[\max_{i=1,2,\ldots n}(m_i + 1)\right]^{-1} \tag{12}$$

where n is the number of clusters and m_i represents the member nodes of i the cluster head. Thus, the clusters with a minimum number of member nodes would require less scheduling time for data aggregation and hence, results in less packet delivery delay. Simulation results show that the ICWAQ algorithm exhibits better performance in terms of maximizing network lifetime and minimizing network transmission delay. However, the centralized clustering approach of ICWAQ algorithm requires resource rich BS with high computational capabilities.

Ari et al. [45] proposed an energy proficient routing protocol called ABC-SD for cluster-based WSNs. It addresses both clustering and routing issue in WSN by exploring the foraging behavior of an artificial bee colony. The clustering algorithm of ABC-SD protocol is a centralized control algorithm in which BS administers the CH election by exploiting a trade-off between communication links quality and energy consumption within the cluster and thereby evaluates a weighted sum based multi-objective fitness function for the efficient assignment of sensor nodes to the CHs. However, the routing procedure of ABC-SD protocol is a distributed approach in which cost function for the efficient route selection is evaluated by exploiting a trade-off between energy-efficiency and hop count. Simulation results show that the ABC-SD protocol exhibits significant improvement in network lifetime, network coverage, and packet delivery ratio under the variable network topology. Moreover, the controlled flooding method in ABC-SD protocol significantly reduces the control overheads.

5.4 Evolutionary algorithm (EA)

EA is used for complex and large sample space problems, but in which sample space is not precisely defined. It deals with the multiple set of candidate solutions known as population and executes in an iterative manner to generate an optimal solution [46]. In this section, we discuss the existing evolutionary algorithms such as GA, NSGA-II, and SPEA proposed in the recent literature.

5.4.1 Genetic algorithm

GA is an evolutionary algorithm which imitates the evolution process to generate optimized solution iteratively. The flowchart of the execution of GA is shown in Fig. 7. It initiates with the set of the randomly generated population of individuals, called chromosomes, where each chromosome represents an array of genes. The fitness function of each chromosome is evaluated based on the particular problem and the chromosomes associated with high fitness value are elected for the reproduction process in the next generation. During reproduction, the chromosomes recombine through a crossover operation to reproduce new children. Crossover is a genetic operation which merges the genetic components of two parents to generate new offspring. After crossover, a mutation operation is performed on the selected chromosomes to generate new children by randomly changing the genes of individual chromosomes. In this way, a new sequence of genes produced using crossover and mutation operations would replace the parent chromosomes with least fitness value. This procedure is repeated until an optimum solution is achieved.

In order to alleviate multi-constrained routing problems, a special class of GA known as multi-objective genetic

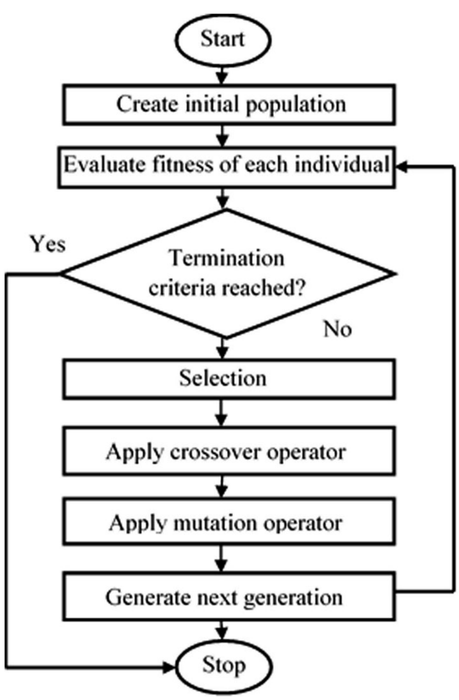


Fig. 7 Flowchart of genetic algorithm

algorithm (MOGA) have been introduced by [47]. MOGA is a Pareto based optimization algorithm and evaluates an optimal solution for two conflicting objectives. However, Non dominated Sorting Genetic Algorithm-II (NSGA-II) is perceived as the most efficient multi-objective evolutionary algorithm (MOEA). NSGA [49], sorts the population on the basis of non-domination and has the capability to maintain the population diversity among all the non-dominated individuals at less computational complexity. MNSGA-II modifies the existing NSGA-II by adopting a dynamic crowding distance to compute pareto optimal solution. It provides more uniformly distributed solutions in a less computational time as compared to NSGA-II [45].

5.4.2 Strength pareto evolutionary algorithm (SPEA)

An SPEA [48] achieves optimal solutions by maintaining an archive containing a set of nondominated individuals. Like NSGA-II, SPEA uses the dominance concept to promote elitism, but here a strength value is evaluated for every non-dominated individual in both population and archive. After all the individuals have assigned a Pareto-strength, the fitness value is generally estimated on the basis of Pareto-strength of non-dominated solutions. The individuals with high fitness values are first achieved and then the mating selection is applied using binary tournament on the previously assigned fitness values, in order to fill the offspring vector, which is then subject to recombination and crossover operators.

EkbataniFard et al. [49] proposed NSGA-II based QoS protocol for routing in two-tiered WSNs. In the two-tiered WSNs, high power relay nodes are considered as CHs which route the aggregated data towards the sink node by satisfying the application specific QoS requirements such as E2E delay, energy utilization, and reliability through crossover and mutation operation. Crossover operation is utilized to create new routing tree and mutation operation is used to create a new path in routing tree. This multi-objective optimization algorithm in the proposed routing protocol provides error free data transmission from the CHs to the sink. Simulation results show that the proposed routing protocol performs better in terms of various QoS parameters such as delay, energy efficiency, and reliability as compared to the existing multi-objective routing protocols.

Murugeswari et al. [50] proposed a multi-objective QoS routing approach in wireless mesh networks (WMN). The proposed approach integrates MNSGA-II and analytic hierarchy process (AHS) to formulate the multi-constrained QoS routing problem into multi-objective routing for optimal route selection. It determines the connectivity among the sensor nodes by evaluating the status of a link in terms of expected transmission count (ETX). Furthermore, in the case of high mobility scenario, the proposed approach does not require any repair function to fix the broken paths and also avoids the redundancy of nodes towards the destination. Through the extensive simulation, the authors show that the proposed approach outperforms in terms of throughput and transmission delay under the variable network density and node mobility. Nevertheless, MNSGA-II algorithm in the proposed approach increases computational complexity and communication overheads of the routing protocol.

Magaia et al. [51] proposed SPEA based multi-objective approach to address the QoS routing problem in WMSNs. It determines an optimal path by providing a trade-off between two conflicting objectives namely, minimizing delay and minimizing Expected Transmission Count (ETX). The ETX metrics in the proposed approach represents an estimation of the expected total number of transmissions essential for successful data packet delivery. These link status metrics evaluate high-quality paths and integrates the effects of asymmetry in link loss ratios, and interference between successive links of the path. Simulation results show a significant reduction in transmission delay and packet loss ratio in comparison to DSR and HTLC-MeDSR algorithm, especially in variable network topology and node density scenarios. However, it does not consider residual energy of the sensor nodes for making a routing decision, which leads to high energy consumption.

To address the reliable data delivery issue of the existing hierarchical routing protocol in UWSNs, Faheem et al. [52] proposed a novel QoS aware evolutionary cluster-based routing protocol (QERP) for real-time UWSN-based applications. The clustering approach of QERP organizes small-sized clusters into a connected hierarchy in an attempt to uniformly disseminate the energy and the data traffic load among the sensor nodes. The multi-hop routing approach in QERP determines optimal next hop node towards the sink node by considering area, residual energy and E2E delay of the node. This greedy routing approach maintains reliability and avoids data path loops to ensure successful data transmission towards the sink node. Moreover, during the sensor node failure, a dynamic power adjustment approach and its routing table determines an optimal relay node to restore the network connectivity and significantly reduces the probability of packet loss in highly dynamic underwater environments. Simulation outcomes show that QERP decreases network delay, and energy utilization and increases packet delivery ratio in comparison to VBF and DBR routing approaches. However, it does not consider the impact of node density, excessive noise and high interference in UWSN applications.

5.5 Fuzzy logic

FL is a mathematical technique able to do reasoning based on the estimated human thinking. Unlike, a classical set theory where the outputs are either true or false, FL creates intermediate values based on inference rules and linguistic variables. The architecture of fuzzy logic system comprises of three fundamental modules, namely, fuzzifier defuzzifier, and inference engine as depicted in Fig. 8. The fuzzifier takes crisp values as the system input and returns a fuzzy degree of membership corresponding to each crisp value. The inference engine maps the fuzzified system inputs to the corresponding fuzzy sets with the assistance of a fuzzy rule base. It assigns membership degree to each fuzzy set which is characterized by a linguistic term, like "high", "low", "medium", "small" and "large". In defuzzifier, the results obtained from the inference system are transformed into the crisp values through defuzzification process. There are several defuzzification methods such as averaging method, and centroid method. However, the execution of fuzzy logic requires minimum system development cost, design time, and computational memory [53].

Minhas et al. [53] introduced a multi-objective online routing algorithm based on fuzzy logic called FMOLD for delay sensitive WSN applications. It determines the optimal path by providing a trade-off between two conflicting objectives, i.e., maximizing network lifetime and minimizing routing delay associated with source node. It defines fuzzy membership function independently for each objective and then, evaluates the multi-objective output function by aggregating the individual objectives through ordered fuzzy averaging (OFA) operator as given by Eq. (13).

$$\mu^{ij} = \beta \times \min\left(\mu^{ij}_{lt}, \mu^{ij}_{md}\right) + (1-\beta) \times \left(\frac{\mu^{ij}_{md} + \mu^{ij}_{md}}{2}\right) \tag{13}$$

where μ^{ij} is the fuzzy multi-objective membership function of edge $e(v_i, v_j)$, μ^{ij}_{lt} is fuzzy membership function for network lifetime, μ^{ij}_{md} is the fuzzy membership for the delay and $\beta \in [0,1]$ is a constant. Once the scalar value is obtained, a weight w is assigned to edge i,j by using the following equation

$$w_{ij} = 1 - \mu_{ij} \tag{14}$$

After assigning weights to the nodes, the multi-objective path is determined by utilizing Dijkstra's algorithm. Simulation results show that FMOLD outperforms in minimizing the data transmission delay in comparison to FML algorithm. However, it generates high control overheads during the data transmission process.

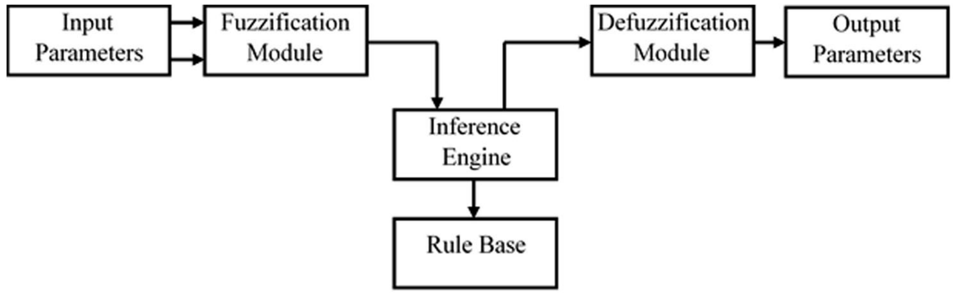


Fig. 8 Fuzzy logic system

Gaddour et al. [54] proposed an FL based QoS-aware routing protocol called OF-FL for Low Power and Lossy Networks (LLNs). The OF-FL protocol considers multiple routing metrics including E2E delay, hop count, residual energy, and link quality to determine the optimal neighbor node. Simulation results show that OF-FL protocol exhibits a significant reduction in the average hop count and the network delay while maximizing the network lifetime. However, it suffers from large computation and control overheads while making the routing decision.

Priya et al. [55] introduced a multi-constraint, multi-objective routing approach called FMMQR to provide guaranteed reliability and on-time data delivery regardless of unreliable communication links and restricted resource. This is achieved by introducing fuzzy 'A-star' algorithm in the proposed approach which considers both energy and bandwidth constraints. Each node in FMMQR protocol is associated with a guidance list, used to determine the best next hop node for data messages transmission. For broadcast messages transmission, each node employs fuzzy rules which considers traffic load, link quality, and residual energy. Moreover, the overhearing nature of broadcast messages reduces the effort to determine the active duration of sensor nodes while transmission. For routing unicast messages, each sensor node employs a modified fuzzy A star approach that considers residual energy, traffic load and hop count to balance the energy consumption load. Simulation results show a significant reduction in redundant data transmission and active duration of the sink node while maximizing the network lifetime under the multiple sinks scenarios.

5.6 Reinforcement learning

RL is a machine learning approach in which the agents perform a necessary action to improve the long-term reward. The agent model of RL algorithm usually consists of State, Action, and Reward. At each step of correlation between the agent and the dynamic environment, the agent receives the status of a current state, 's', of the environment as an input and decides to perform an action, 'a', according to its acquired knowledge as shown in Fig. 9. The elected

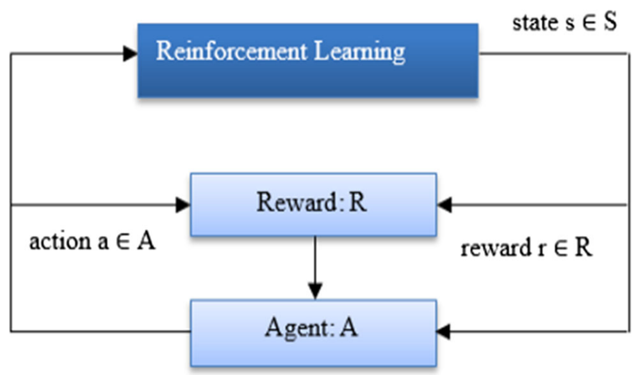


Fig. 9 Reinforcement learning

action may change the environmental state and this state transition information is routed through a scalar reward, r towards the agent node. This reward signifies the appropriateness of performing an action $a \in A$ in state $s \in S$. As time passes, the learning agent correlates each state-action pair with the highest reward based on its past experience and hence, achieves optimal performance evaluation.

Q-learning is the most commonly used RL technique in literature. The reward function of In Q-learning algorithm is expressed in terms of Q-value which is updated when an action *at* is performed at state *st*. The future total reward is calculated by using Eq. (15):

$$Q(st+1, at+1) = Q(st, at) + \lambda, [r(st, at) - Q(st, at)] \tag{15}$$

where $r(st, at)$ represents the immediate reward of executing an action *at* at state *st*, and $0 \le \lambda \le 1$ represents the learning rate which indicates the speed at which the learning will happen. This learning approach can be realized in a distributed environment like WSNs, where each sensor node attempts to execute specific actions that are supposed to maximize its long-term rewards [56, 57].

Liang et al. [58] proposed an RL based QoS routing protocol called RL-QRP for WBANs. The RL-QRP utilizes dispersed Q-learning mechansim which considers packet delivery ratio and E2E delay associated with the nodes as the link quality indicators for optimal path selection. After routing the data packet, source node gets either a positive or negative reward from its neighboring nodes. Both reward and expected future reward update the Q-value associated with the sensor node, which is used to make the future decisions for optimal path selection. Moreover, the flexible nature of the protocol makes it adaptable towards the highly dynamic traffic. Simulation results show a significant reduction in packet loss ratio and average E2E delay when compared to the QoS-AODV protocol, especially in high mobility scenario. However, this work is based on independent distributed reinforcement learning (IndRL) which does not support global optimization and limits its use to small-scale networks only.

Jin et al. [59] proposed Q-learning based delay-aware routing algorithm known as QDAR to maximize the lifetime of UWSNs. By employing a Q-learning approach, the QDAR algorithm determines a global optimal path by taking into account the propagation delay and the residual energy of the sensor nodes. Consequently, each node evaluates its energy-related cost function $ce(e^i_{res})$ and delay-related cost function $ct(t_{ij})$ and forwards the collected information to sink node through the data-ready packet.

$$ce\left(e^i_{res}\right) = 1 - \frac{e^i_{res}}{e^i_{ini}} \tag{16}$$

where e^i_{res} and e^i_{ini} are remaining energy and initial energy of node respectively.

$$ct(t_{ij}) = 1 - \frac{1}{t_{ij} + 1} \tag{17}$$

where t_{ij} is the packet transmission delay associated with node i and j. The adaptive detouring path mechanism in QDAR algorithm exploits trades-off between residual energy and delay in order to achieve load balancing among the sensor nodes and maximizes the lifetime of the network. Moreover, the unique packet structure of QDAR algorithm has the ability to quickly adapts to the dynamic underwater conditions. Simulation results show significant improvement in the residual energy of sensor nodes while maintaining minimum path delay. However, it does not consider energy utilization cost due to retransmission under dynamic network conditions.

5.7 Bird mating optimization

BMO is an evolutionary-based searching algorithm, inspired by the mating behavior of birds in nature [60, 61]. The steps associated with the execution of the BMO algorithm is given as follows:

1. *Initialization* It initiates with the population of individuals referred as the society and each member in the society called bird, represents a feasible solution in the population.
2. *Fitness value* The quality of each bird in a society is evaluated by inserting its values into the fitness function. It represents the ability of the bird to bring more food and memorize the routes towards the destination.
3. *Ranking* The birds are ranked according to their fitness values attained in step 2.
4. *Classification* The individuals having the most promising genes are considered as females, while the others are selected as males. The female birds are individuals with a higher score in society and can be grouped into two classes: parthenogenetic and polyandrous. However, the male birds have the lower score in society and can be classified into three groups: monogamous, polygynous, and promiscuous. Each bird makes utilization of one of these approaches to breed.
5. *Breeding* The female birds in society attempts to raise broods and pass on better genes to her broods by mating with predominant males probabilistically.
6. *Replacement* Each bird reaches the optimal solution by incorporating its brood to the society based on the fitness evaluation. If the brood has better quality in the search space, the bird will abandon the society and the brood will restrain in it, otherwise, the brood will abandon, and the bird will remain in the society.
7. *Final selection* The entire process repeats iteratively until a predefined number of generations is reached. Consequently, the bird with superior quality is selected as the final solution in the society.

In order to provide reliable communication in a smart grid environment, Faheem and Gunjor [62] proposed a dynamic clustering-based energy efficient and QoS-aware routing protocol known as EQRP. The EQRP exploits the intelligent searching and mating behavior of birds to address the clustering and routing problems in WSN. The fitness function of the clustering mechanism in EQRP constructs uniform size cluster in order to ensure stable load balancing among the CHs. It also includes link quality associated with sensor nodes to ensure reliable data transmission in the smart grid. However, the routing mechanism of EQRP takes into account the inter-cluster distance, the hop count, the residual energy, and the proximity degree for relay node selection in an attempt to balance the intra-cluster and inter-cluster energy consumption load among the CHs. Simulation results show that the EQRP provides a significant reduction in packet loss rate, energy consumption, E2E delay, and memory utilization in the network. Moreover, it addresses the fault tolerance routing issue by electing the backup route in case of any primary route failure.

Table 2 Comparison of CI techniques based QoS-aware routing protocols

Computational intelligence technique	Protocols	QoS mechanism	Transmission mode	Node type	Merits	Limitations	Scope of application
ACO	ACO-QoSR [30]	Multiple routing metrics	Multi-hop	Homogenous	Mitigates stagnation Highly adaptable towards dynamic network conditions	Does not investigate the retransmission cost	Delay sensitive applications
	AntSensNet [31]	Service differentiation Multipath routing Multiple routing metrics	Multi-hop	Heterogenous	Supports energy efficient video transmission Prevents network congestion	High complexity	Surveillance
	DAWMNet [32]	Multipath routing Multiple routing metrics	Multi-hop	Homogenous	Ensures reliability and load balancing Adaptable towards the dynamic network topology	Not preferred in small scale networks	Industrial WSN
	EAMR [33]	Multipath routing Multiple routing metrics	Multi-hop	Homogenous	Provides robustness to mobility and traffic Achieves load balancing	High communication overheads	Surveillance
	EAQHSeN [34]	Service differentiation	Multi-hop	Heterogenous	Low routing and control overheads Rapidly adapts to node mobility	Scalability cannot be assured	Surveillance
	IACO-MS [35]	Mobile sink Clustering	Single-hop	Homogenous	Faster convergence rate	Does not investigate the issue of link failure	IOT
PSO	QoS-PSO [38]	Multiple routing metrics	Multi-hop	Homogenous	Adaptable towards the dynamic network topology	Requires mechanism to effectively handle high mobility	Surveillance
	ECPSOA [39]	Mobile sink Multiple sinks Multiple routing metrics	Multi-hop	Homogenous	Ensures robustness Addresses communication overheads issues	High computational complexity	IOT
	GMDPSO [40]	Mobile sink Multiple routing metrics	Multi-hop	Homogenous	Faster convergence rate Provides robustness to sink mobility	High cost of route recovery mechanism in terms of time and computation	MWSNs
	EPMS [41]	Mobile sink Clustering	Single-hop	Homogenous	Improves resource utilization Addresses hot spot problem	Does not investigate the issue of routing overheads and link failure	Surveillance
ABC	ICWAQ [44]	Clustering	Single-hop	Homogenous	Improves network lifetime and transmission delay	Requires resource rich BS	Delay sensitive monitoring
	ABC-SD [43]	Clustering Multiple routing metrics	Multi-hop	Homogenous	Addresses scalability and overhead issues	Does not investigate the issue of link failure	Disaster management

Table 2 (continued)

Computational intelligence technique	Protocols	QoS mechanism	Transmission mode	Node type	Merits	Limitations	Scope of application
EA	NSGA-II [49]	Multiple routing metrics	Multi-hop	Homogenous	Provides error free data transmission	High computational complexity Slow convergence	WMSN
	MNSGA-II [50]	Multiple routing metrics	Multi-hop	Homogenous	Avoids redundancy of nodes Improves convergence	High computational complexity and communication overheads	MSN
	SPEA [51]	Multiple routing metrics	Multi-hop	Homogenous	Considers the impact of link loss ratio and interference to ensure reliability	High processing requirements	WMSN
	QERP [52]	Multiple routing metrics	Multi-hop	Homogenous	Ensures robustness and fault-tolerance issues	Slow convergence speed	UWSN
FL	FMOLD [53]	Multiple routing metrics	Multi-hop	Homogenous	Implements trade-off between network lifetime and network delay	High control and routing overheads	Delay sensitive sensing
	FMMQR [54]	Multiple routing metrics Multiple sinks	Multi-hop	Homogenous	Minimizes redundant data transmission Supports both broadcast and unicast transmission	Does not adaptable towards the network dynamic	Environment monitoring
	OF-FL [55]	Multiple routing metrics	Multi-hop	Homogenous	Maximizes network lifetime	Large computational and control overheads	LLNs
RL	RL-QRP [58]	Multiple routing metrics	Multi-hop	Heterogenous	Highly flexible towards dynamic network traffic	Restricts to small scale network only	WBAN
	QDAR [59]	Multiple routing metrics	Multi-hop	Homogenous	Ensures load balancing	Does not consider the retransmission cost	UWSN
BMO	EQRP [62]	Clustering Multiple routing metrics	Multi-hop	Homogenous	Ensures reliable data transmission Addresses route failure issue	High cost of load balancing in terms of time and computation	Smart Grid

Table 3 Comparative analysis of reviewed protocols

Computational intelligence technique	Protocols	QoS metrics								Year
		Energy efficiency	Delay	Reliability (PDR)	Throughput	Network lifetime	Adaptivity	Low control overheads	Robustness	
ACO	ACO-QoSR [30]	✔	✔	✔			✔	✔		2006
	AntSensNet [31]	✔	✔	✔		✔	✔	✔		2010
	DAWMNet [32]		✔	✔			✔	✔	✔	2013
	EAMR [33]	✔	✔	✔			✔	✔		2015
	EAQHSeN [34]	✔	✔	✔			✔	✔		2017
	IACO-MS [35]	✔	✔		✔	✔				2017
PSO	QoS-PSO [38]	✔	✔	✔			✔			2012
	ECPSOA [39]	✔	✔	✔			✔	✔	✔	2015
	GMDPSO [40]	✔	✔	✔			✔	✔	✔	2016
	EMPS [41]	✔	✔		✔	✔				2017
ABC	ICWAQ [44]	✔	✔			✔				2012
	ABC-SD [45]	✔		✔	✔	✔		✔		2016
EA	NSGA-II [49]	✔	✔	✔						2010
	MNSGA-II [50]		✔	✔	✔		✔			2016
	SPEA [51]		✔	✔	✔				✔	2015
	QERP [52]	✔	✔	✔			✔		✔	2018
Fuzzy logic	FMOLD [53]	✔	✔			✔				2009
	FMMQR [54]									2014
	OF-FL [55]	✔	✔	✔		✔				2017
RL	RL-QRP [58]	✔	✔	✔			✔	✔		2008
	QDAR [59]	✔	✔			✔	✔			2017
BMO	EQRP [62]	✔	✔	✔	✔	✔	✔		✔	2018

6 Analytical discussion and summary of CI based QoS-aware routing protocols

This section provides a brief summary and a comparative analysis of CI-based QoS-aware routing protocols in WSN as shown in Tables 2 and 3. Table 2 highlights the primary QoS mechanisms, transmission mode, merits, limitations, and the scope of application of the reviewed QoS-aware routing protocols. Table 3 gives the comparative analysis of different CI-based QoS-aware routing protocols on the basis of QoS evaluation parameters. In this comparative analysis table, tick mark indicates that the given routing protocol improves the corresponding QoS metrics in WSN.

After the comprehensive analysis of reviewed protocols, it can be seen that most of the routing protocols employ multiple techniques to provide QoS support at the network layer in WSN. In this regard, a concluding graphical representation on various QoS mechanisms employed by the reviewed routing protocols is presented as shown in Fig. 10. This section will also facilitate the researchers to quickly analyze various computational intelligence algorithms discussed in this paper and select the appropriate

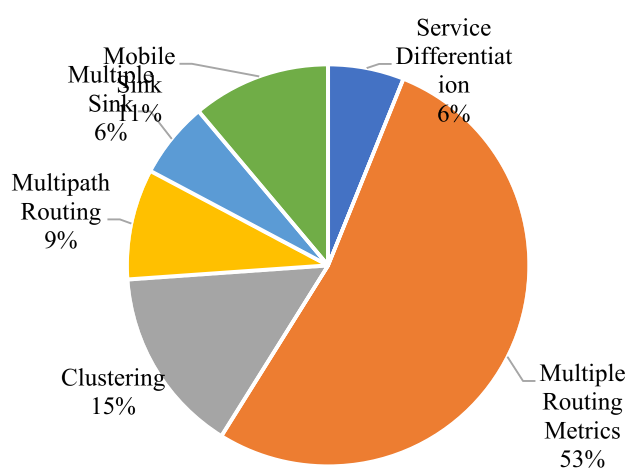


Fig. 10 QoS mechanisms used by articles

intelligent algorithms based on their advantages and limitations as shown in Table 4 to provide QoS support at network layer in WSN. ACO is the most widely adopted intelligent algorithm by the researchers that provide QoS support to heterogenous traffic load through multi-constrained and multipath routing. In case of sink mobility,

Table 4 Summary of computational intelligence techniques

CI techniques	Advantages	Disadvantages
Fuzzy logic	The execution of FL requires minimum system development cost, design time, and computational memory	FL induces large computation complexity and control overheads while making the routing decision
	FL based routing algorithms in WSNs have the potential for dealing with conflicting situations without requiring any complex mathematical model	Fuzzy rules are not adaptable towards the network dynamics and required to be re-learnt with dynamic network conditions
Ant colony optimization	ACO is the most preferred CI technique for multi-constrained routing due to its distributed nature	ACO lacks the necessary information to find optimal paths at the beginning and takes more time to converge
	It has the ability to withstand with the highly dynamic environment	It generates high routing overheads in form of forward and backward ants
	It distributes network traffic load among all the sensor nodes through multipath routing	
Particle swarm optimization	PSO is another most popular CI technique used in WSNs due to its ease of implementation on hardware or software, fast convergence rate, and highly optimal solution	The iterative nature of PSO does not make it suitable for real-time applications
	PSO based routing protocols show significant improvement in terms of robustness and adaptability towards the dynamic sink mobility and the network topology while maintaining minimum communication overheads	PSO has large memory constraint which requires resource-rich base station
Artificial bee colony	ABC algorithm achieves global optimization through exploration which is executed by artificial scouts, while attains local optimization through exploitation which is managed by onlookers and employed bees	ABC has slow convergence problem due to the random solutions generated by the components
	It effectively solves the optimization problem related to multimodal and multivariable functions	
Reinforcement learning	RL based routing protocols find an optimal path through experiences and rewards which do not require any precise network state information for optimal route reservation	RL algorithm needs sufficient time to explore and learn the network dynamics which degrades network delay and throughput in the initial period of simulation
	They are fully distributed, easy to implement, scalable, and flexible towards the changing network topology	The length of the learning period in RL depends on network size and node's density, which increases exponentially with increase in the number of nodes
	They are robust against the node and link failure	
Evolutionary algorithm	EA-based routing protocols efficiently solve multi-objective routing problem where predetermined information about the network such as topology, density, and size is not required	EA-based routing protocols have high computational complexity and processing requirements in order to collect sufficient information at the sensor nodes before determining an appropriate relay node for data forwarding
	The inbuilt parallel nature and ability to optimize hard real-time problems make GAs suitable for data aggregation mechanism	EA has slow convergence speed which restricts its implementation in real-time applications
		It lacks the ability to deal with changing network topology and communication link failures
Bird mating optimization	BMO algorithm has comparatively fewer parameters to evaluate the fitness function	For complicated problems, BMO algorithm is not efficient in identifying the high performance regions of a solution space. It shows premature convergence or poor efficiency
	It has the ability to locate most promising regions with better solutions	

PSO algorithm can be used due to its ease of implementation and fast convergence rate. However, ABC and BMO are best suited for implementing multi-objective clustering in WSN. In addition, FL works well for the conflicting routing situations which do not require any complex mathematical model. Finally, EA and RL can also be employed by various routing protocols to support application-specific QoS requirements in WSN.

7 Conclusion and future research directions

The recent advancements in QoS provisioning techniques to support wide variety of applications such as smart grid, IOT, military surveillance and Body Area Networks has become a great matter of concern for the researchers worldwide. This survey has introduced a novel taxonomy on research related to QoS provisioning techniques at the network layer in WSNs. The QoS-aware intelligent routing protocols discussed in this survey reflect the importance of CI-techniques in WSN. A comparative analysis of reviewed protocols along with advantages and research issues is also presented. It is observed that the existing QoS-aware routing protocols have various limitations such as slow convergence, network disruption, unreliable delivery, and high computational complexity. Hence, more effective and adaptive QoS-aware routing protocol should be designed in order to meet the application-specific QoS requirements of resource-constrained WSN. In future, following work can be explored to overcome the research issues of the existing QoS-aware routing protocols.

- *Cross-layer approach* The heterogeneous traffic (video streaming, still images, audio, scalar data) has multiple QoS constraints, which are addressed by considering various routing metrics like delay, reliability, packet loss rate, congestion, energy consumption, and hop count during the optimal path selection. These routing metrics are highly influenced by MAC layer parameters such as congestion factor, channel access delay, queuing delay, type of data traffic and duty-cycle duration. Thus, MAC-aware routing metrics need to be developed in an attempt to jointly enhance the QoS performance of resource-constrained WSN.
- *Mobility* Most of the existing QoS-aware routing protocols are designed for static WSN. The increasing interest in medical care and mission-critical applications require the use of mobile nodes. However, mobility in sink/sensor nodes induces various issues such as dynamic topology variation, energy management, and mobility overheads. Hence, these issues need to be addressed in order to give efficient QoS assurance in mobile sensor networks.
- *Error-free transmission* To effectively handle the delay and reliability-constrained applications, such as battlefield communication, military surveillance, disaster management, and healthcare monitoring, where secure and error-free transmission of data packets is required. But the issues such as node's misbehaviour attack, packet tempering, and black hole attack are the hurdles. Thus, trust-aware routing needs to be developed to support QoS in a highly reliable environment.
- *Fault-tolerant routing* The high probability of sensor node failure due to quick battery exhaustion or some hardware components malfunction may lead to information loss among the sensor nodes and the BS. However, in hierarchical WSN, the failure of a CH node disrupts the network connectivity not only with its associated member nodes but also with the neighbor CHs nodes. Therefore, a fault-tolerant routing mechanism needs to be considered to re-establish the network connectivity.
- *Hybrid intelligence* Most of the conventional intelligence algorithms have some shortcomings such as slow convergence, high learning period, and sensitive to initial value and it is often very difficult to obtain the desired result with one of these algorithms alone. In order to address these issues associated with optimization algorithms, the future research should focus on the development of hybrid intelligence algorithms [9]. Little research has done so far in this area, such as Fuzzy-ABC [63], Fuzzy-ACO [64], GA-ACO [65], and Fuzzy-GA [66] etc. and it requires to be further explored.
- *Multi-channel routing* Multi-channels routing brings great potential for maximizing the network concurrency and throughput by allowing the parallel transmissions over multiple channels. It also has ability to deal with high bandwidth data in WMSNs. Although several solutions have been proposed at the physical and MAC layers to address the issues associated with multi-channel access networks, further research on developing efficient routing approaches that exploits the potential benefits of multi-channel access capability to promote efficient data delivery in WMSNs.

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